CAST SHADOW RECOGNITION IN COLOR IMAGES

Elena Salvador and Touradj Ebrahimi
Signal Processing Laboratory (LTS),
Swiss Federal Institute of Technology (EPFL),
CH-1015 Lausanne, Switzerland
e-mail: {elena.salvador,touradj.ebrahimi}@epfl.ch

ABSTRACT

Shadows are often integral parts of natural scenes and their identification is an important task in image analysis. In this paper, we propose an algorithm for recognition of shadows cast by objects on the scene's background. The proposed approach is based on the use of color information by means of photometric invariant color transformations. The method is divided into two levels: first, object and shadow edges are extracted from the RGB components and only object edges from the invariant features; then, edges are filled and the obtained masks are combined to extract shadow regions. Simulation results show that the proposed algorithm is robust and efficient in detecting shadows within a set of assumptions on the scene that makes the method's applicability wider than that of state-of-the-art methods.

1 INTRODUCTION AND RELATED WORK

Shadows are generated when objects occlude light from a source of illumination. They are a frequent occurrence in images. The identification of shadows in computer vision is an important task which has received relatively limited attention. On one hand, shadows are a valuable source of information about the shape and the relative position of objects in the scene represented in a digital image, as well as about the characteristics of surfaces and light sources. On the other hand, their presence may hinder the performance of object segmentation and interpretation systems for applications such as satellite imaging and image databases that require the identification of objects. A shadow often has the same effect as a segmentation error on the performance of such systems. Moreover, the information about the shape and the color of segmented objects may be distorted by shadows. Shadows should be therefore identified in order to provide a correct description of the scene.

Two different approaches can be found in the literature in the field of shadow detection in still images. The first is based on models of the scene and the illumination, the second on shadow properties.

The first approach comprises methods which are designed for specific applications, such as aerial image understanding [3, 7, 10, 15], surveillance [9] and image rendering [14]. They exploit *a priori* knowledge of the three-dimensional geometry of the scene, the objects, and the illumination. These geometry-based approaches have two major limitations. Simple rectilinear models can be used only for simple objects, as for instance buildings and vehicles. In addition, the *a priori* knowledge of the illumination and the 3-D geometry of the scene is not always available. These techniques are therefore only applicable to the specific application they have been designed for.

The second approach overcomes these limitations by exploiting shadow's geometry, intensity and color properties. Luminance is exploited by analysing edges [16], histograms [11, 13], or texture [1]. Both geometry and luminance are exploited in [8]. Here, a shadow identification and classification algorithm for gray-scale images is presented. The method is based on the analysis of shadow intensity and geometry in an environment with simple objects and a single area light source[1]. Only simple scenes, without occlusions between objects and shadows, are considered.

A physical–based approach to distinguish material changes from shadow boundaries in chromatic images is presented in [5]. In [2], a method that uses color ratios for analyzing edges with regard to whether they are due to a shadow or a material change is described. A system that combines color information and geometry information to detect cast shadows is described in [4]. The method is applicable to more complex scenes when compared to those analyzed in [8], but it presents a very strong limitation that makes it impossible to use to automatically recognize shadows. An active observer is introduced who is allowed to cast its own shadow. From this shadow the direction of the light source is empirically calculated. By using this information, shadows are confirmed among the extracted candidate shadow regions.

The approach we present in this paper allows to extend the range of applicability of the work of [8] and [4]

[1] An area light source is a source of illumination presenting a certain extent (in contrast to a point light source).

and overcome some of their limitations, as regards illumination conditions and the need of an active observer. It is based on shadow properties, and shows how the invariance properties of some color transformations can be easily exploited to extract cast shadows in digital images. It is also applicable when no *a priori* knowledge of the scene is available and when objects of different types are present.

The paper is organized as follows. In Sec. 2, the proposed shadow detection method is described. Experimental results are presented in Sec. 3, and in Sec. 4 we draw some conclusions.

2 PROPOSED METHOD

We propose a system which detects shadows cast by objects on the scene's background by using color information. Assumptions on the scene are considered. Shadows are assumed to be cast on a flat, or nearly flat, nontextured surface. No restriction to the number of light sources and their extension is considered, as long as generated shadows remain simple and do not interfere with each other. Objects and shadows are supposed to lie within the image. The method is applicable also in the case of occlusion between objects and shadows.

Color information is exploited by considering color features that show invariance properties with respect to changes in the illumination conditions, that is to shadows and shading. They are introduced in Sec. 2.1.

The method can be divided into two levels. First, object and shadow edges are extracted from the image. Then, edges are filled and shadow regions are extracted. Section 2.2 describes the two levels of the detection process.

2.1 Invariant Color Models

Photometric invariant color features are functions which describe the color configuration of each image point discounting shadings, shadows and highlights. They are invariant to a change in the imaging conditions, such as viewing direction, object's surface orientation and illumination conditions.

Among the traditional color features, normalized rgb, hue (H) and saturation (S) are shown to be invariant to shadows and shading considering dichromatic reflection and white illumination [6]. In addition to these well-known color spaces, new invariant color models, $c_1c_2c_3$ and $l_1l_2l_3$ are also proposed [6].

We have evaluated the behavior of all the invariant features cited above, namely rgb, H, S, $c_1c_2c_3$ and $l_1l_2l_3$, in the proposed shadow recognition system. The best results are obtained using the $c_1c_2c_3$ model, that has been adopted in our method. The $c_1c_2c_3$ color invariant features are defined as follows:

$$c_1 = \arctan\left(\frac{R}{max(G,B)}\right) \tag{1}$$

$$c_2 = \arctan\left(\frac{G}{max(R,B)}\right) \tag{2}$$

$$c_3 = \arctan\left(\frac{B}{max(R,G)}\right) \tag{3}$$

for R, G, and B representing the red, green, and blue color components of each pixel in the image.

2.2 Shadow recognition

The first level of analysis toward the identification of shadows is the extraction of object and shadow contours. Object and shadow edges are extracted from the RGB components of the image, which are sensitive to variations in the illumination caused by shadows. Only object edges are obtained from the photometric invariant features. In the second level of the analysis, edges are filled and the difference between the obtained regions is computed to extract the shadow regions.

2.2.1 Color Edge Detection

Edge detection on the RGB components of the image allows to extract both object and shadow contours (Fig. 1 (b)). Contours are extracted via a color edge detector. The edge map is obtained by applying a Sobel operator separately on the three color channels of the image. The color edge map results from a logical OR-connection operation on the three edge maps corresponding to the three color channels.

Similarly, color edge detection is performed in the invariant space to extract a map which does not contain the edges corresponding to shadow boundaries, that is a map that contains only object edges (Fig. 1 (c)). Contours in the invariant color features, in fact, correspond to material changes. The color edge map is, as before, the result of a logical OR-connection operation on the edge maps obtained with the Sobel operator on each color component in the invariant space.

To improve edge delineation, a post-processing is applied on the edge maps. An elimination of isolated noise-induced edge pixels is performed. This is done by performing a labeling of the edge map and by removing those labels whose total number of pixels is below a fixed percentage α of the maximum number of connected edge points.

2.2.2 Shadow Extraction

In the second level of the analysis, shadow regions are extracted from the image. The RGB edges are filled in order to obtain a binary mask that represents object and shadow regions in the image. The invariant features edges are filled in order to obtain a binary mask representing only objects in the scene. Shadow pixels are extracted as those pixels which belong to the first binary mask and do not belong to the second. Finally, a morphological post-processing (an erosion followed by a dilation operation) is applied to the final mask to refine the results.

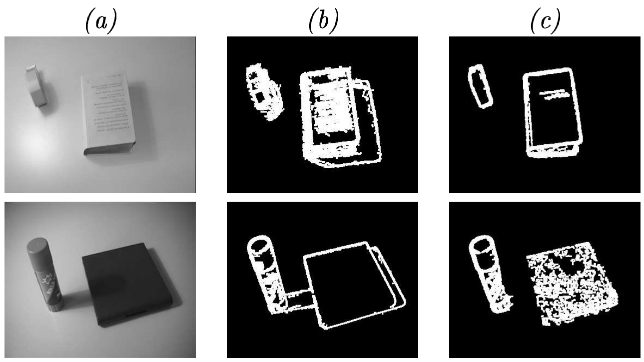

Figure 1: Edge detection on *RGB* (b) and photometric invariants (c).

	RGB	$c_1c_2c_3$
Image1	0.02	0.14
Image2	0.05	0.12
Image3	0.03	0.09
Image4	0.07	0.07
Image5	0.03	0.07

Table 1: Value of the thresholds for color edge detection on the different test images.

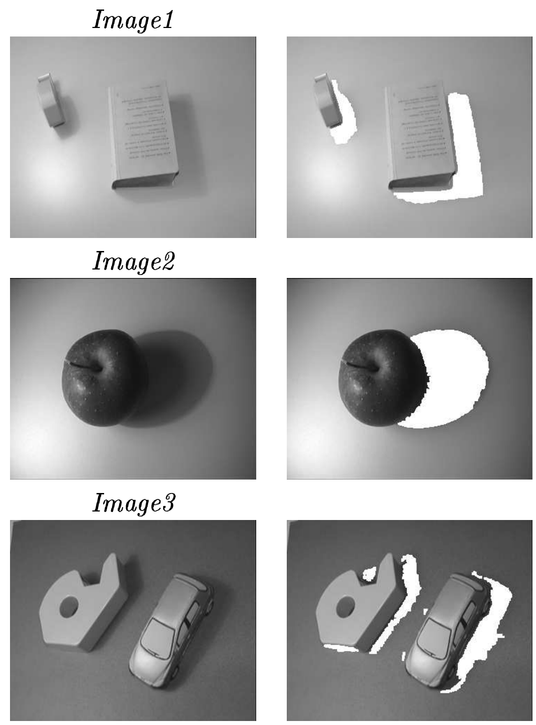

Figure 2: Shadow detection results.

3 RESULTS

The proposed method has been tested on different test images, which respect the hypotheses commented in Sec. 2. The first columns of Fig. 2 and 3 show a selection of these images. Objects are made of different materials and present different colors.

The edge detection process on the *RGB* components of the image and on the $c_1c_2c_3$ features requires the setting of a threshold τ for the binarization of the edge map. The threshold determines the sensitivity of the edge detector and has been manually determined in this paper. The values of τ for the different test images are shown in Table 1. The values for the invariant features maps are higher than those for the *RGB* components. In the first case, a lower sensitivity of the edge detector is required to reduce the number of edge points detected, due to noise, far outside the object contours. In the second case, a higher sensitivity allows to obtain a map where edges form as much as possible closed contours. For the post-processing of the edge maps, the value of the threshold α described in Sec. 2.2.1 is set to 10% for all the tests.

The second columns of Fig. 2 and 3 show the shadow regions extracted by the proposed method for the displayed test images, superimposed on the original images. The results show that shadow regions have been correctly identified. It is possible to notice that in the case of *Image4*, on the dark object on the right, and *Image 5*, on the marker in the lower left corner, some object points have been misclassified as shadow points. These errors are due to the instability of the invariant color features for low values of saturation and intensity. For a correct color edge detection in the invariant space, in fact, saturation and intensity values have to be larger than 5% of their total range [6]. Errors in the color edge detection for *Image4* are shown in Fig. 1 (c). To overcome this problem, a way to process low-confidence regions should be investigated, as proposed in [12].

However, thanks to the use of color information, and not only intensity, the method has correctly distinguished in *Image4* the dark object from its shadow. This would not have been possible for techniques that exploit only luminace properties of shadows for their identification.

In *Image5* the gray object on the top left corner of the image has been entirely misclassified as a shadow region. This is due to the fact that there is a tradeoff between the amount of invariance and the expressiveness of the color models. Therefore, the reduced discriminative power of the invariant features has prevented the edge detection step to identify the edges of the above mentioned object.

4 CONCLUSIONS

We described an efficient method for detection of cast shadows based on the use of color information. In the

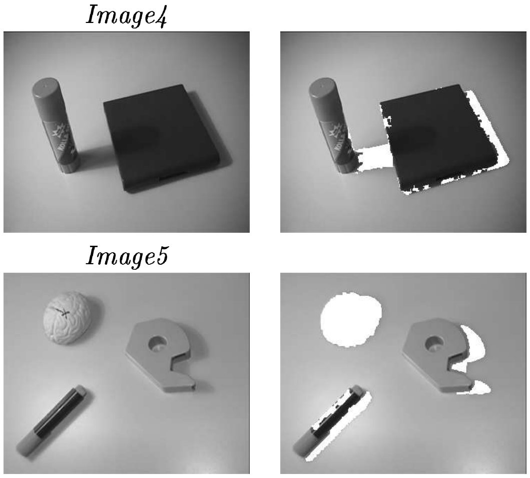

Figure 3: Shadow detection results.

first level of the algorithm, edge detection on the *RGB* components of the image gives a map that contains both object and shadow edges. Only material changes, that is object edges, are obtained by edge detection on the photometric invariant features. In the second level of the strategy, the edge maps are filled and combined to extract shadow regions. The efficiency of this approach for detection of cast shadows was demonstrated through application to a number of typical images.

Several directions can be considered to extend the work described in this paper. The proposed technique has been designed to detect a particular type of shadows, namely, cast shadows. Other types of shadows such as self shadows can be detected by exploiting the properties of invariant color transformations. The detection of self shadows is important for a correct description of object color. Another important direction of research is that of shadow detection in video. In this case, the additional temporal information can be exploited.

References

[1] M. Adjouadj, *Image analysis of shadows, depressions, and upright objects in the interpretation of real world scenes*, Proc. Int. Conference on Pattern Recognition, pp. 834–838, 1986.

[2] K. Barnard and G. Finlayson, *Shadow Identification using Colour Ratios*, IS&T/SID 8th Color Imaging Conference: Color Science, Systems and Appl., pp. 97–101, 2000.

[3] M. Bejanin, A. Huertas, G. Medioni and R. Nevatia, *Model Validation for Change Detection*, 2nd Int. IEEE Workshop on Applications of Computer Vision, Los Alamitos, USA, pp. 160–167, 1994.

[4] G. Funka-Lea and R. Bajcsy, *Combining Color and Geometry for the Active, Visual Recognition of Shadows*, Proc. Int. Conference on Computer Vision, pp. 203–209, 1995.

[5] R. Gershon, A. D. Jepson, and J. K. Tsotsos, *Ambient illumination and the determination of material changes*, J. Opt. Soc. Am. A, 3 (10), pp. 1700–1707, 1986.

[6] T. Gevers and A. W. M. Smeulders, *Color-based Object Recognition*, Pattern Recognition, 32, pp. 453–464, 1999.

[7] R. B. Irvin and D. M. McKeown, *Methods for exploiting the relationship between buildings and their shadows in aerial imagery*, IEEE Trans. Systems, Man, Cybernetics, 19, 1564–1575, 1989.

[8] C. Jiang and M. O. Ward, *Shadow Segmentation and Classification in a Constrained Environment*, CVGIP: Image Understanding, 59 (2), pp. 213–225, 1994.

[9] D. Koller, K. Danilidis and H.-H. Nagel, *Model-Based Object Tracking in Monocular Image Sequences of Road Traffic Scenes*, International Journal of Computer Vision, 10 (3), pp 257–281, 1993.

[10] Y. Liow and T. Pavlidis, *Use of shadows for extracting buildings in aerial images*, Computer Vision Graphics Image Processing, 49, pp. 242–277, 1990.

[11] M. Nagao, T. Matsutyama, and Y. Ikeda, *Region extraction and shape analysis in aerial photographs*, Computer Vision Graphics Image Processing, 10, pp. 195–223, 1979.

[12] F. Perez and C. Koch, *Toward Color Image Segmentation in Analog VLSI: Algorithm and Hardware*, International Journal of Computer Vision, 12 (1), pp. 17–42, 1994.

[13] J. M. Scanlan, D. M. Chabries, R. Christiansen, *A Shadow Detection And Removal Algorithm for 2-D Images*, Proc. Int. Conf. on Acoustics, Speech, and Signal Processing, pp. 2057–2060, 1990.

[14] J.-P. Thirion, *Realistic 3D Simulation of Shapes and Shadows for Image Processing*, CVGIP: Graphical Models and Image Processing, 54 (1), pp. 82–90, 1992.

[15] C. Wang, L. Huang, and A. Rosenfeld, *Detecting clouds and cloud shadows on aerial photographs*, Pattern Recognition Letters, 12, pp. 55–64, 1991.

[16] A.P. Witkin, *Intensity-based edge classification*, Proc. Nat. Conference on Artificial Intelligence, pp. 46–41, 1982.